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DataHub sponsored analysis

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Introduction

The primary productivity of phytoplankton in the ocean is largely responsible for the assimilation of carbon into the oceanic environment, and thus in part the removal of carbon from the atmosphere. Because the ocean is thought to be a primary sink for atmospheric carbon, the basin wide and global distribution of oceanic primary productivity is of central importance in the global budget of carbon. To understand the global productivity of the oceans, the interactions between the physical and biological structures must be known. The biological population of the ocean is highly variable both spatially and temporally on all time and space scales. The global nature of this problem then requires the use of satellite instrumentation as the only platform capable of providing coverage on temporal and spatial scales that are appropriated to the assessment of carbon flux in the ocean. The goal of this research is to increase our understanding of the sources of variability in the sea to provide a more accurate assessment of oceanic productivity from ocean color imagery. The objectives of this research are the description of the spatial and temporal distributions and variability of the planktonic community in the sea and primary productivity of that community. To achieve these objectives, remotely sensed data of the spatial and temporal distributions of pigment concentration and sea-surface temperature are required to provide a global description of the seasonal variability of the water column primary productivity.

To address the broader context of the primary productivity of the sea, the physical and biological processes and their variability, including changes in water mass, incident irradiance, nutrients and consequent formation of blooms of difference species of marine phytoplankton and bacteria must be studied. In this investigation, we will use time series of the pigment distributions, taken from the Coastal Zone Color Scanner (CZCS), and of the sea-surface temperature, taken from the NOAA Advanced Very High Resolution Radiometer (AVHRR). These time series will be examined to determine the spatial and temporal statistics of productivity, including the interannual variations that occur in productivity caused by variations in the physical environment.

For this task we have chosen to use monthly composite global maps created from the satellite imagery. The pigment maps are created from the ratios of upwelling radiance at 440, 520 and 550 nm, and have been composited from a data set that is characterized by a sparse data coverage because of the presence of clouds and because of the sampling characteristics dictated by the Nimbus-7 satellite operations. The monthly composite images from the CZCS contain significant regions for which no data exist. Attempts to estimate the global primary productivity of the ocean from these composite images have yielded a preliminary assessment of the net annual flux of carbon from the atmosphere into the oceans to be 3.2 G-tons Carbon per year, based on estimates of the water leaving radiance, and a regression against carbon flux from the work by Mitchell, et al. 1992. To provide a better estimate, and to provide the time series of this flux, we must interpolate the pigment images to provide an estimate of the pigment concentration in regions for which the data is inadequate. Conventional techniques such as bi-linear interpolation and spline fits have given insufficient results because of the large areas of missing data.

The MCSST data product can be used to understand variations in the sea-surface temperature in regions where large data gaps are present because this product has used an interpolated data field

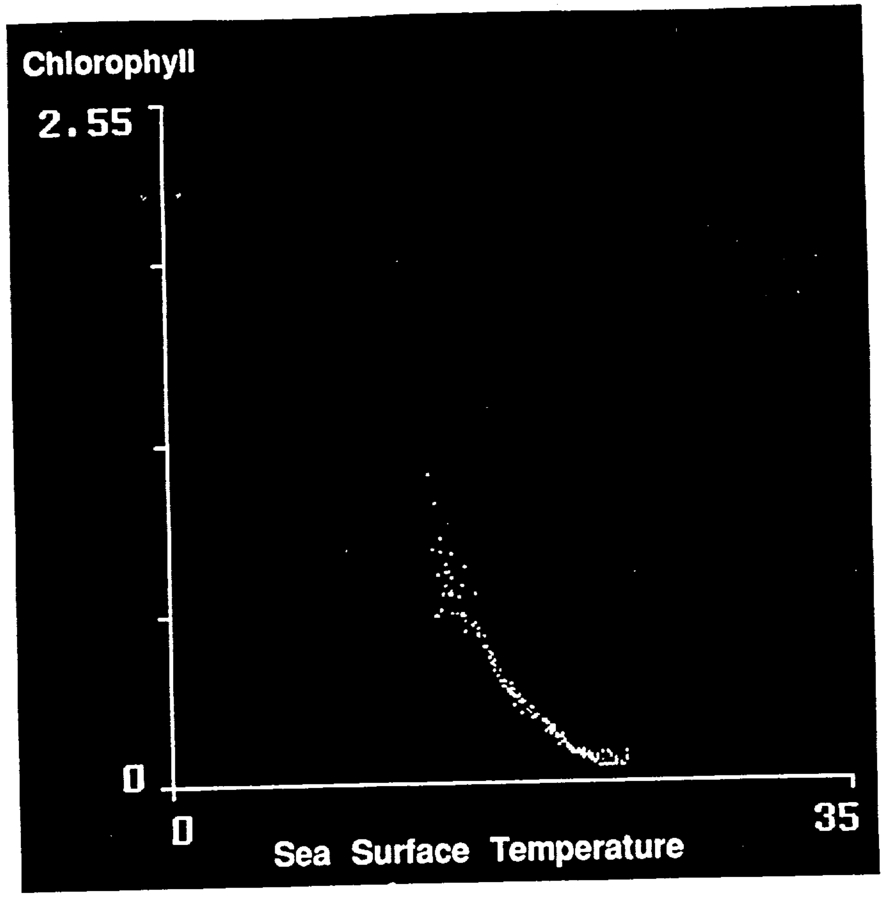

Figure 1. Correlation between chloroplyll and temperature center at 15 degrees north.

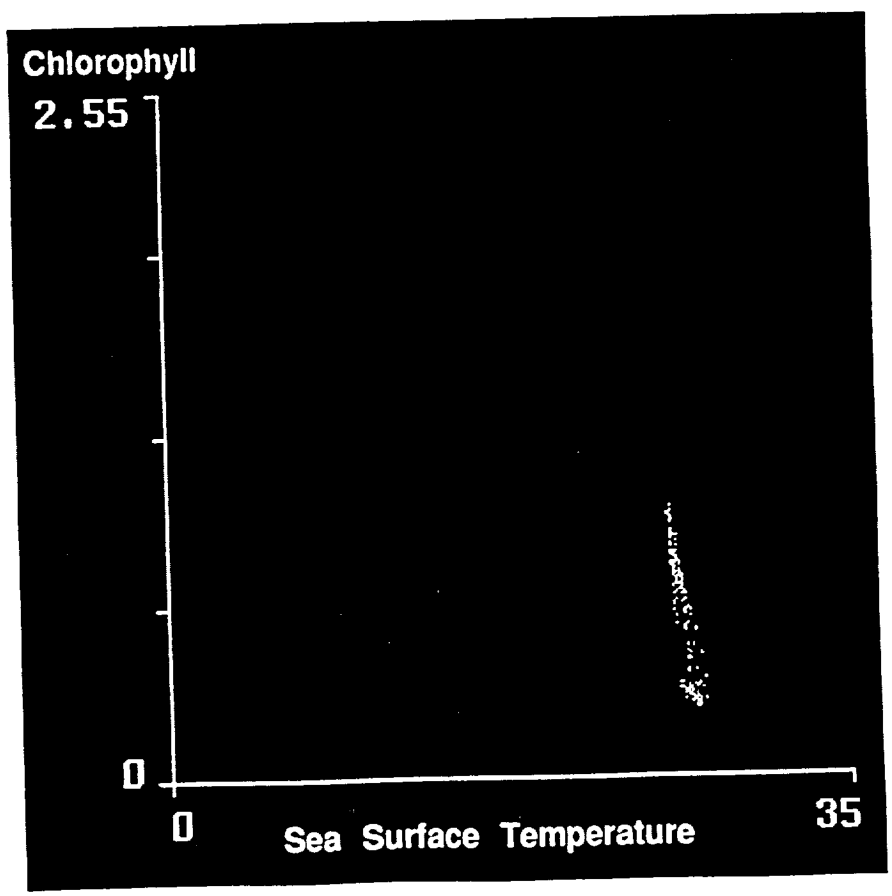

Figure 2. Correlation between chloroplyll and temperature center at 35 degrees north.

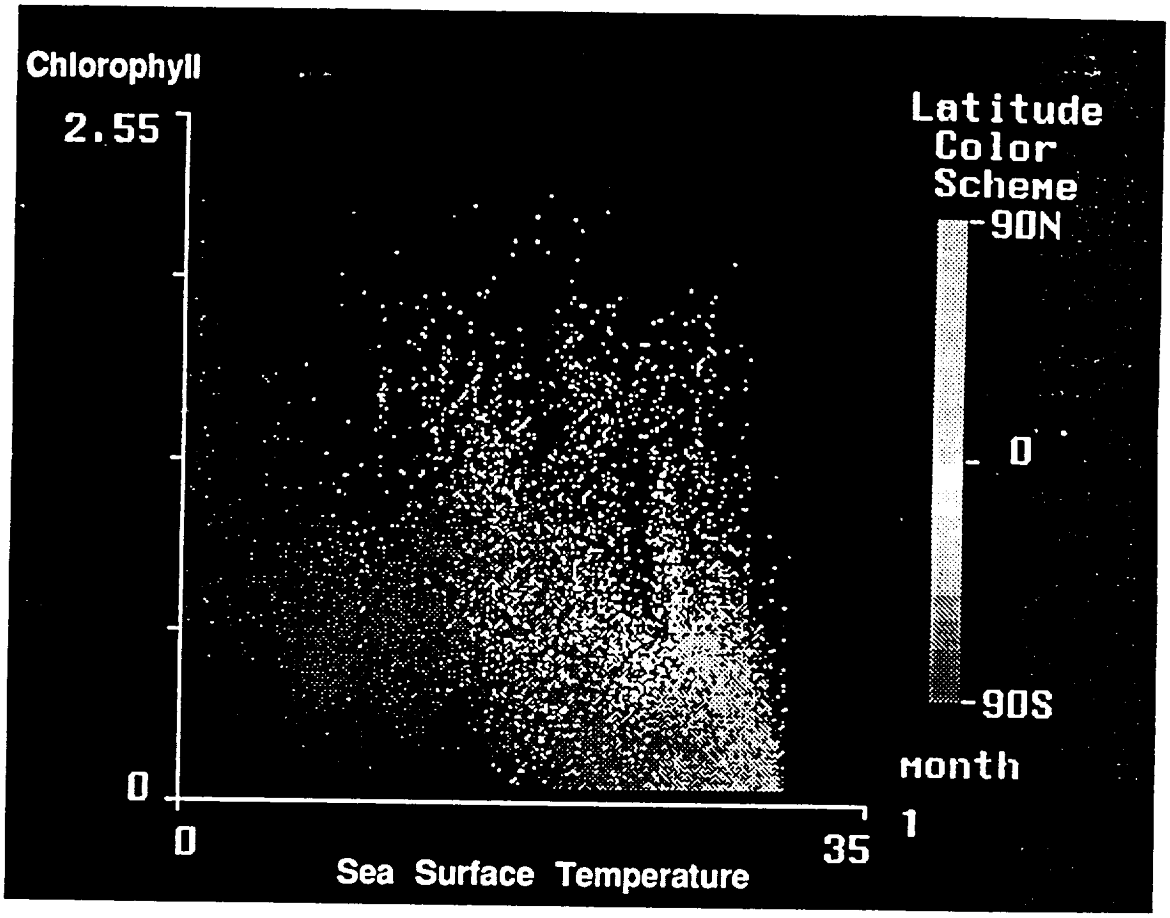

Figure 3. Correlation between chlorophyll concentration and temperature for entire global

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to supply missing data values for regions for which clouds obscure the surface during the time of the monthly composite. To provide internal consistency between the pigment and sea-surface temperature data fields, the same interpolation scheme will be used for both data fields.

The primary productivity of the sea has been shown to be related to both the standing stock of the phytoplankton population, and to the temperature of the sea, which both regulates the metabolism of the planktonic organisms and reflects the nutrient status of the sea through a physical relationship between temperature and nutrients in newly upwelled water. For these reasons, working with Mitchell, et al., we have developed a relationship between the temperature of the sea, the upwelled radiance ratio in the photosynthetic bands, and the primary productivity of the sea. While this relationship is still under investigation, the regressions that have been produced indicate that a strong correlation exists for the flux of carbon through the surface layer, and these relationships will be used to produce the first time series maps of the global flux of carbon in the sea.

Through the primary productivity, the standing stock of phytoplankton, as reflected by the pigment concentration, is also related to the temperature, although in a very complicated manner. It is this relationship that we have exploited in the interpolation of the pigment fields. Figures 1 and 2 indicate two latitudinal regions in the ocean, one at 15 degrees and one at 35 degrees north. In these figures, we illustrate two facts: First that at each latitudinal band, there is a strong correlation between temperature and pigment concentration. Second, that the correlation is very different for these two regions. The global picture for the correlation between temperature and pigment concentration is shown in Figure 3. These results indicate that we may use temperature in the interpolation of the pigment fields, but that the algorithm is both regional and seasonal in nature, leading to an exhaustive computational problem if conventional analysis were to be applied. These facts have led us to investigate different methods for the interpolation of the pigment fields in regions for which sufficient data is not available to provide a satisfactory estimate of the pigment to permit an estimate of the productivity.

The first method that we have examined is the use of a least squares regression using both temperature and pigment for the estimate. This technique will find a matrix transformation mapping spatial averages of temperature and pigment data and latitude values onto the space of pigment values such that the difference between the two sets is minimal in the root mean square sense. The variation of input parameters can be extended to include the square or cube of the spatial variables. These variables were combined in an equation where the coefficients were determined by the least squares technique. This analysis was conducted using the IMSL (International Mathematical Statistical Library) software.

Several polynomials with different variable combinations were used to examine the variability of error produced with each equation. The coefficients of these polynomials describe the contribution of each variable to the predicted pigment value. The results of studies conducted on a restricted data set indicate that a simple linear regression based on the pigment alone gives a satisfactory fit to the data from the trial cases. The results suggest further testing on a significantly larger data set, using multiple iterations of the interpolation process.

The second method uses the methods of a neural-net, coupled with a bi-linear interpolation, using both the temperature and pigment fields to form the estimate of the missing data in the pigment field, and the temperature field alone for the estimate of the missing temperature values. This technique relies on the pigment fields both past and future for the pixel in question, the past and future temperature fields, coupled with a spatial interpolation of the pigment field to produce an estimate for the missing data pixel. The neural-net system is trained on a data set which has both the spatial and temporal coverage appropriate to the data set under investigation, and is used on the global data set for all time. The initial data set is shown in Figure 4, which illustrates the large areas of missing data in the global pigment images. The results of the interpolation are shown in Figure 5, which illustrates the degree to which the fields may be interpolated using this technique. The technique has been verified by removing data from the original data set, applying the technique to regenerate the data, and comparing the original data to that replaced by the artificial intelligence system. Figure 6 describes the correlation between the predicted pigment concentration from the Neural-Net and the pigment concentation from the satellite measurements. The correlation coefficient for this estimate is R2= 0.952 .

For this task we used the most well known neural-net classifier (known as "back-propagation"). Back-propagation was introduced originally (Rumelhard, 1986), it was proposed that the criterion function to optimized using gradient descent. However, it was soon realized that more efficient algorithm and training techniques can be employed; the "momentum" term (Rumelhard, 1986) is the most popular example of such improvements. This techniques incorporated gradient descent and the previous weight change is used to update the weight vector.

We used seven different variables as input and one output into neural-net program. The inputs consist of three from the CZCS pigment field, three from the AVHRR temperature field, and the latitude of the center pixel. Figure 7 shows the lay-out input parameters for back-propagation Neural-net.

The relationship between the global chlorophyll data and the temperature product is not well defined. Neural-nets have shown the ability to handle multi-dimensional data sets with non-linear relationships.

From these experiments, we conclude that the neural net permits the computation of a globally interpolated data field for all time. The results of this study are being evaluated to determine the scientific validity of both techniques.

References

D.E. Rumelhart, G. E. Hinton, and R. J. Williams, 1986: "Learning internal representations by error propagation" in Parallel Distributed Processing. MIT press, Cambridge MA, Chapter 8, 318-362, 1986.

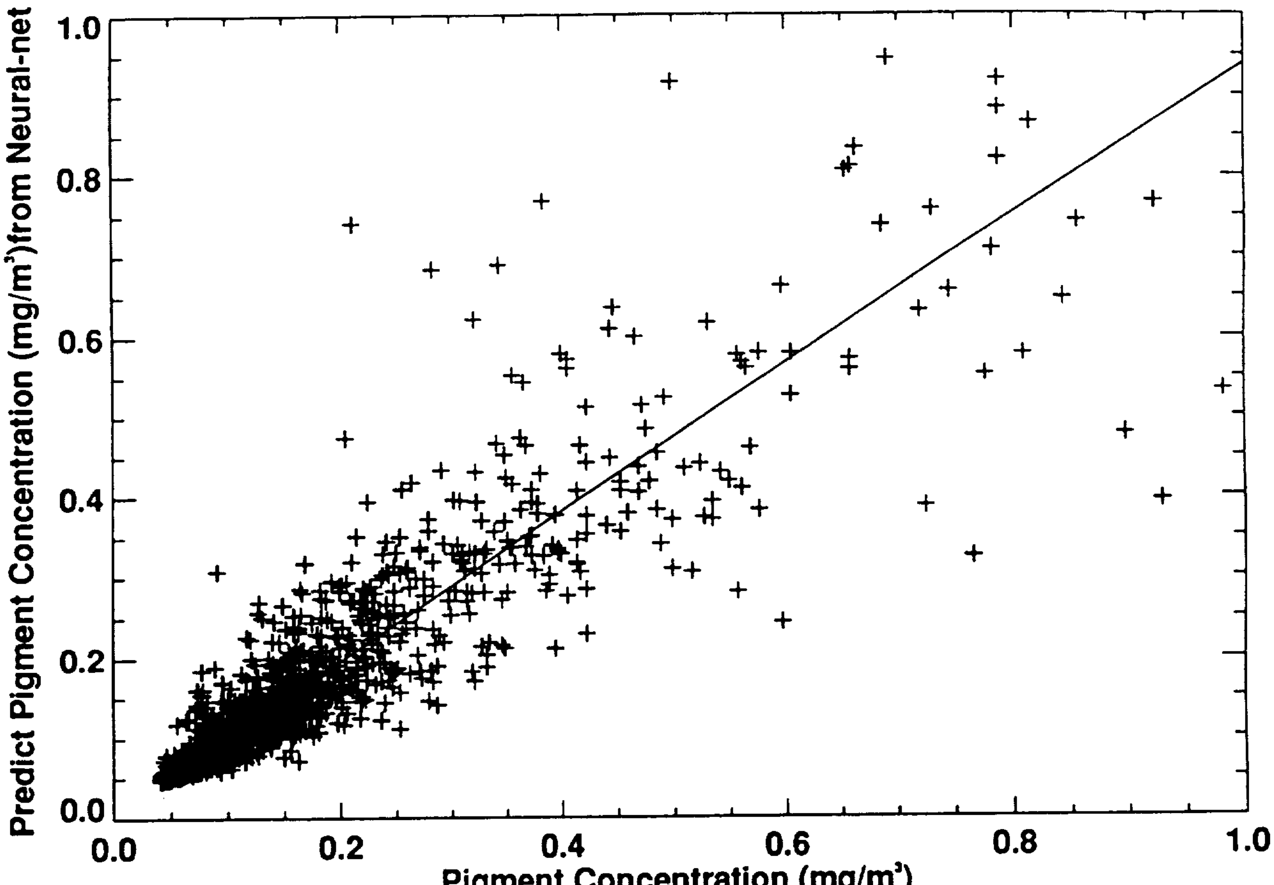

1.0
0.8
0.6
0.4
0.2
0.0
Predict Pigment Concentration (mg/m³)from Neural-net
0.0
0.2
0.4
0.6
0.8
1.0
Pigment Concentration (mg/m³)

Figure 6

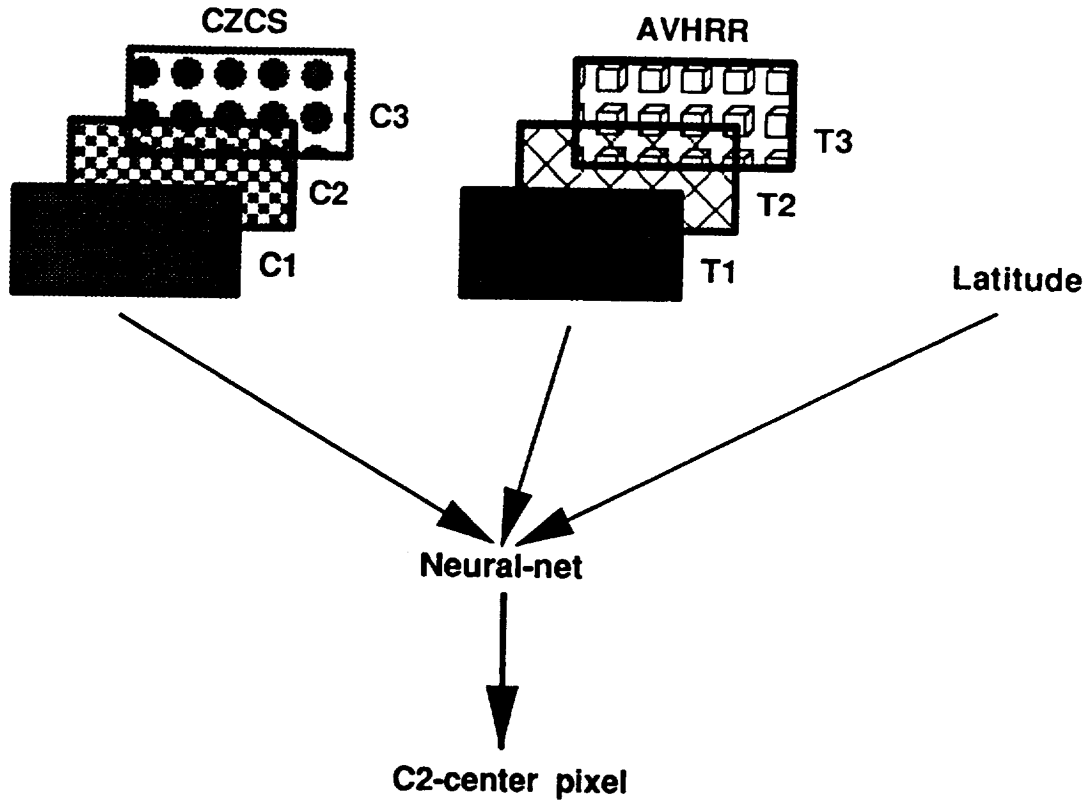
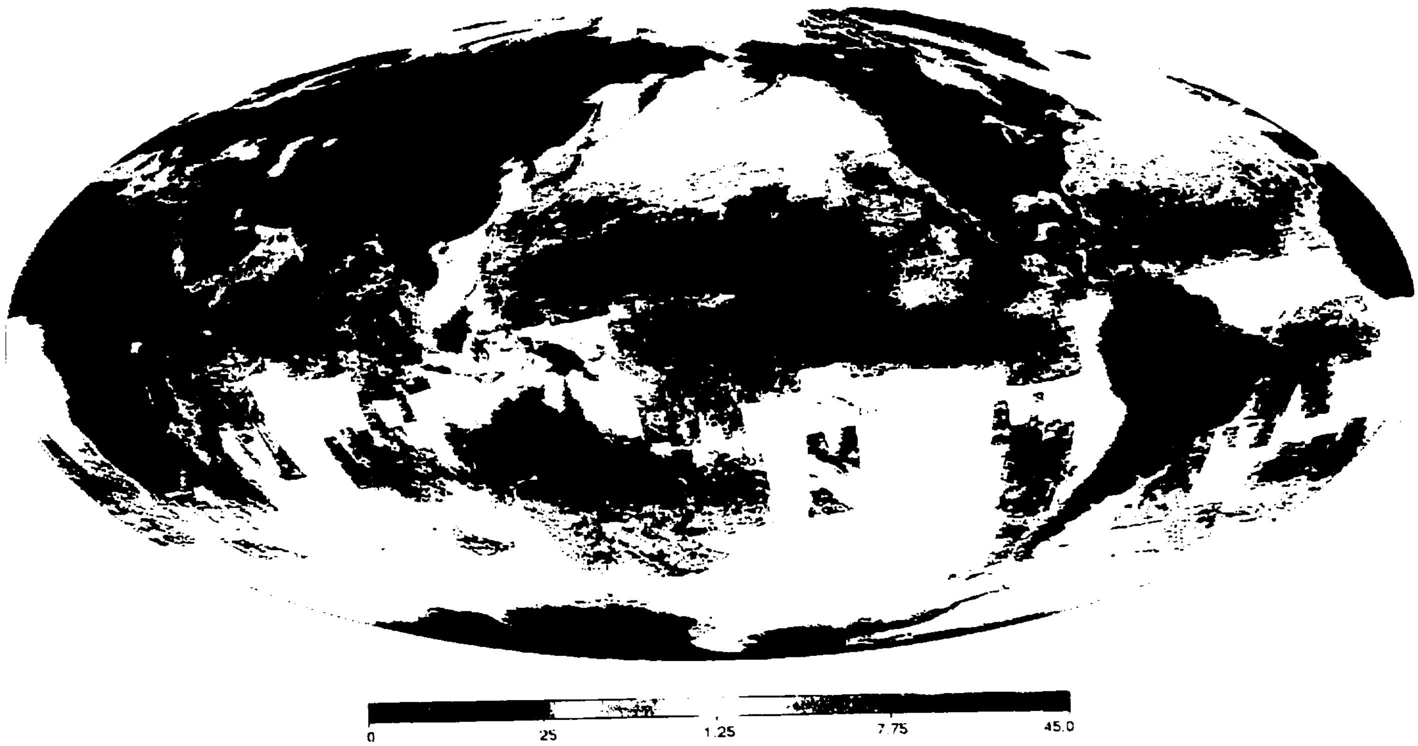
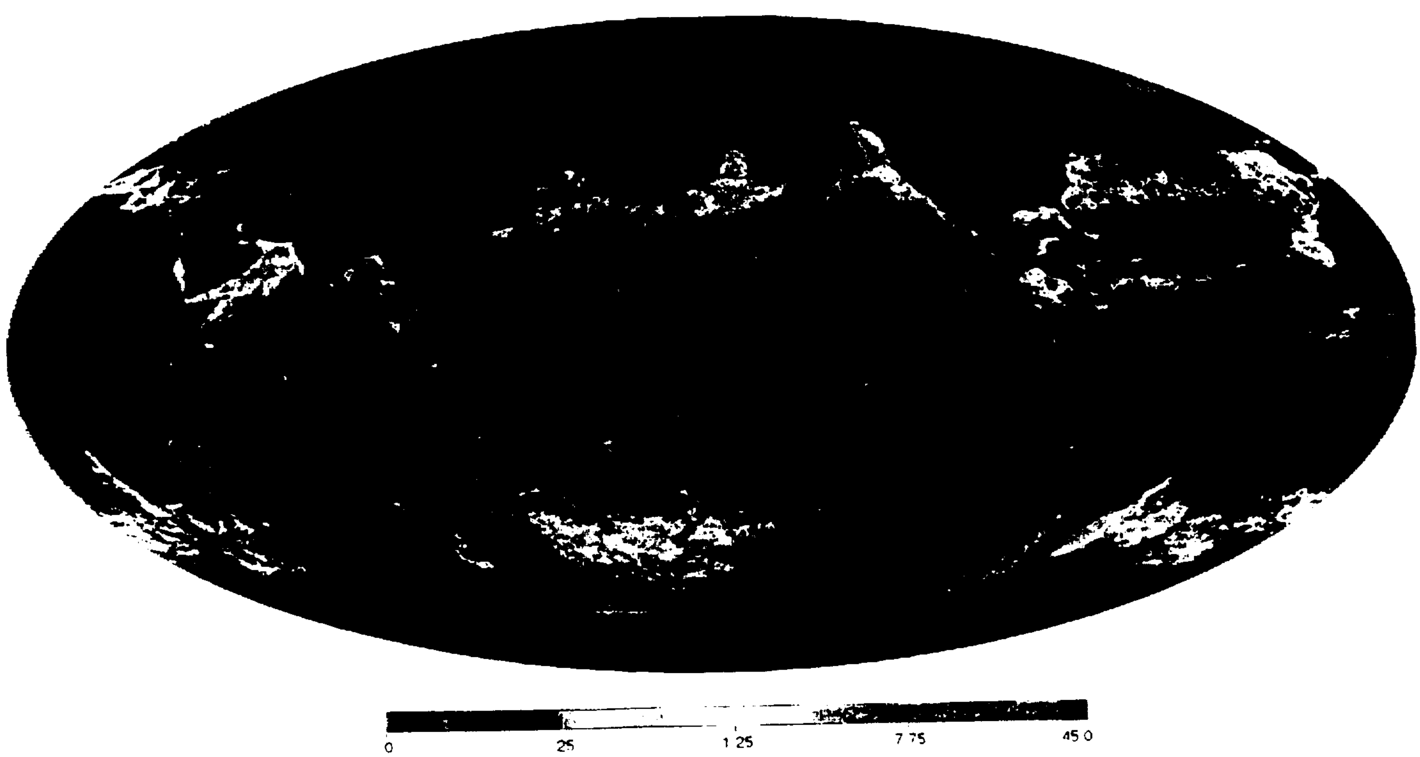


Figure 7. shows input parameters used to to train the neural net. Where C represents Chlorophyll and T for temperature. Each rectangle represents the average pixel for each time slice. Latitude represents the latitude of center images.



CZCS Pigment (mg/m^3) January 1982



Interpolate CZCS Pigment (mg/m^3) January 1982

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